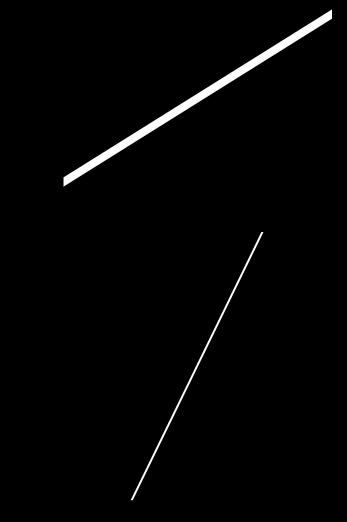
Big data, ML and Al for energy systems

Hendrik F. Hamann Chief Science Officer IBM Research hendrikh@us.ibm.com



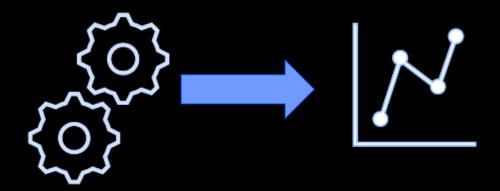
Ever improving, lower cost computation generates big data, which drives machine-learning and AI



Computation & storage & networks

- 50% better performance/year
 - less cost/year

Ever improving, lower cost computation generates big data, which drives machine-learning and Al



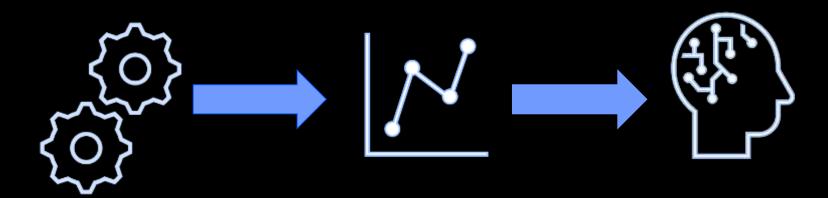
Computation & storage & networks

- 50% better performance/year
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Massive Data

90% of all data created in the last two years

Ever improving, lower cost computation generates big data, which drives machine-learning and Al



Computation & storage & networks

- 50% better performance/year
 - less cost/year

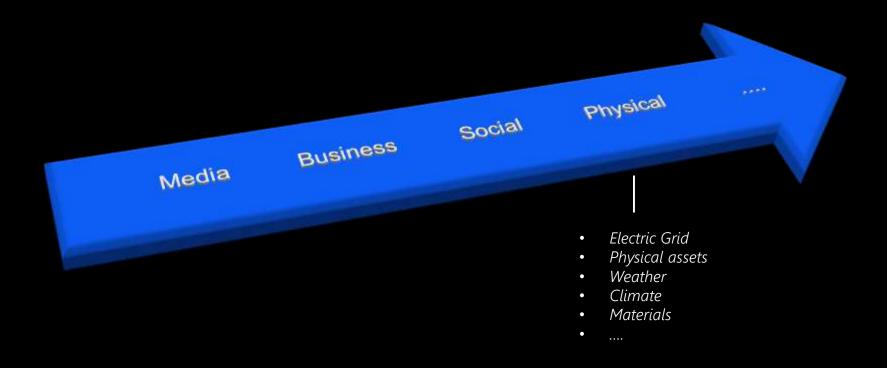
Massive Data

90% of all data created in the last two years

Machine Learning & AI Foundation Models

Already 98% of enterprises already use Al

Digitization is progressing quickly

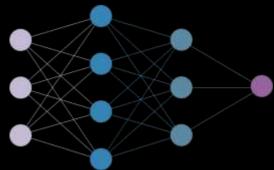


Let's talk Data

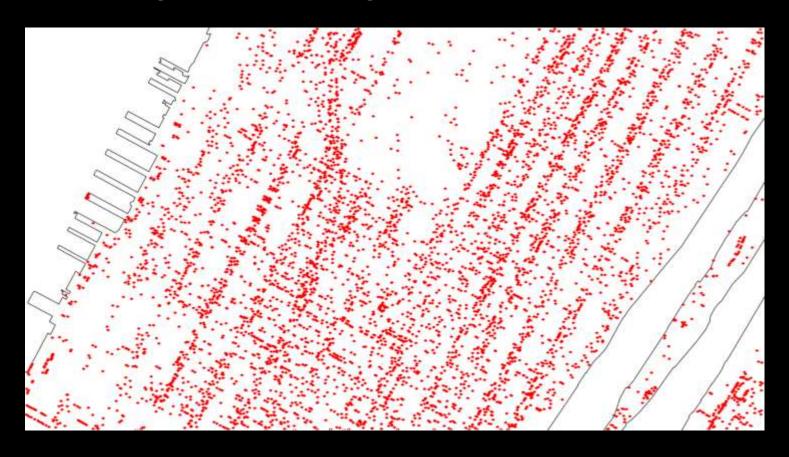


Data Challenges - Various modalities

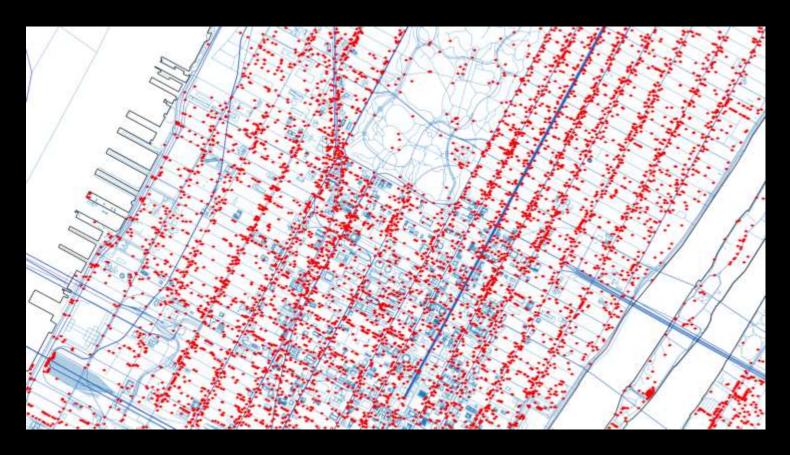
	Sequence	Time series	Geospatial	N-dimensional	
Text					
Image					
Vector					
Audio					



Data Challenges – Creating Context



Data Challenges – Creating Context



Data Challenges – Creating Context



Data Challenges – Gravity

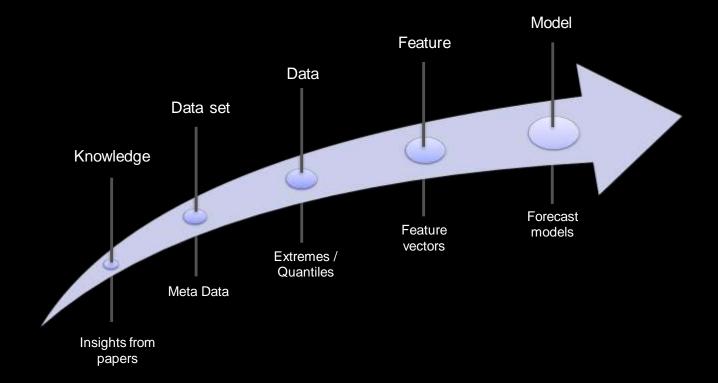


Data Challenges – Gravity vs Entropy

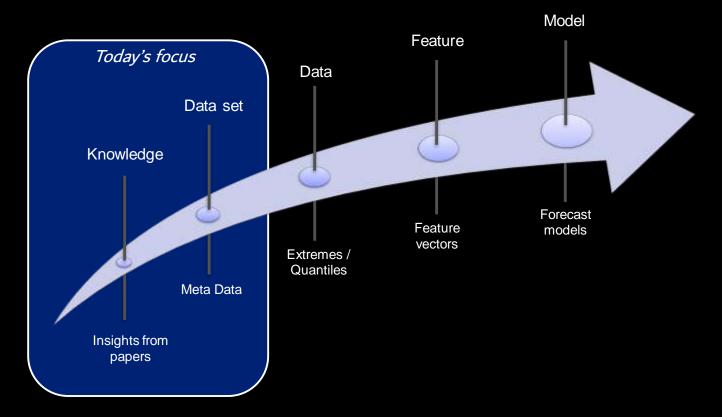




Data Challenges – Lack of Discoverability

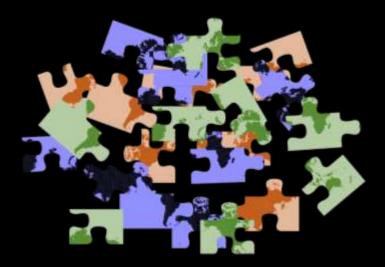


Data Challenges – Lack of Discoverability



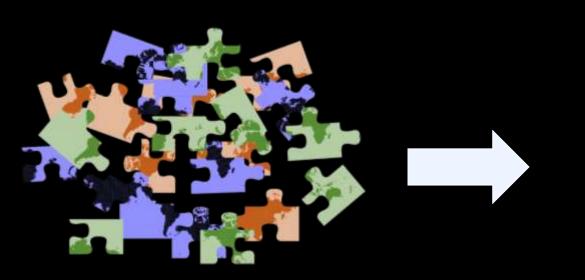
Question – How to envision the next-gen data technology to support Al for energy systems?

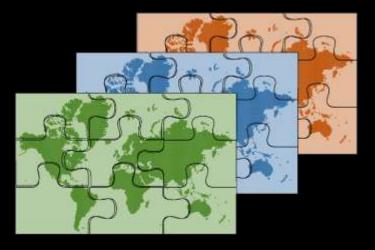
Next Gen Data System



Distributed, massive, multi-modal data

Next Gen Data System

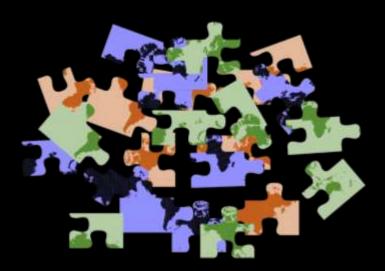




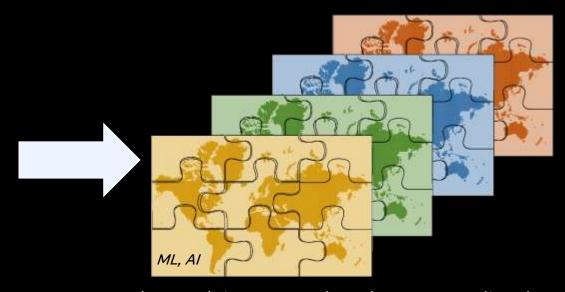
Distributed, massive, multi-modal data

- Federated, integrated and contextualized
 - Scalable search and discovery

Next Gen Data System



Distributed, massive, multi-modal data



- Federated, integrated and contextualized
 - Scalable search and discovery
- Rapid insights (with little data movement)

Innovation and Research opportunities for nextgen data technology to support AI for energy systems

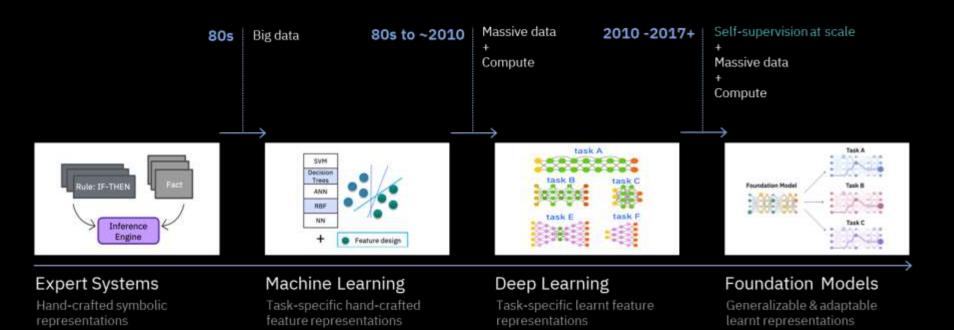
- New federation approaches & distributed computing
- New forms of in-data computation
- Advanced indexing / novel data structures for energy system specific information
- Information discovery (going beyond meta-data)
- New forms of representing logical and physical information



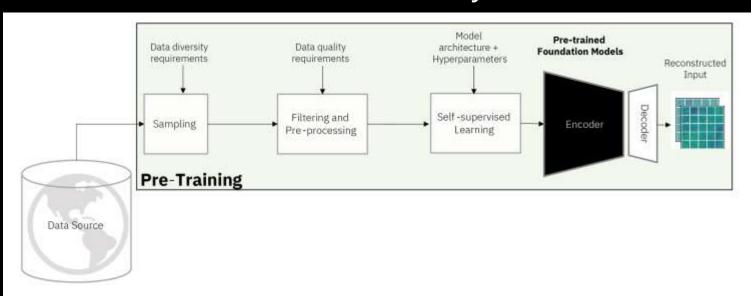
Let's talk ML and Al



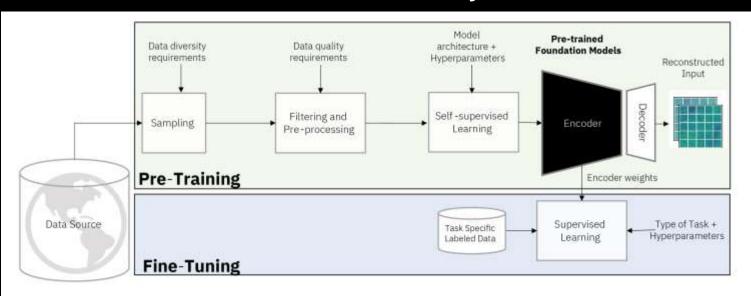
The evolution of AI and the emergence of Foundation Models



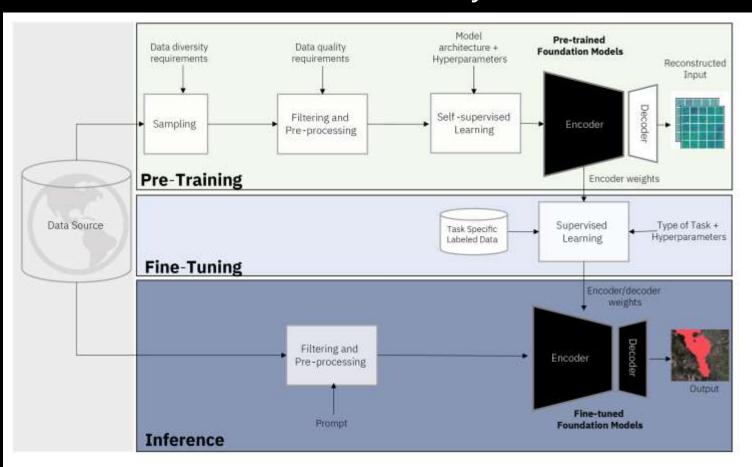
Foundation Models – how do they work?



Foundation Models – how do they work?

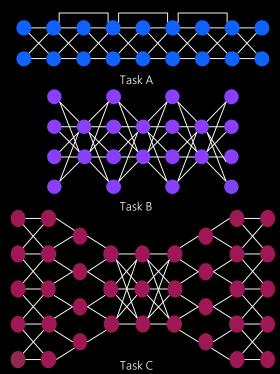


Foundation Models – how do they work?



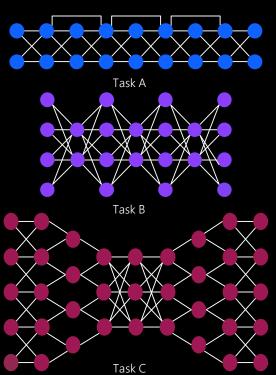
Why Foundation Models?

Classical AI models: Purpose-built and siloed

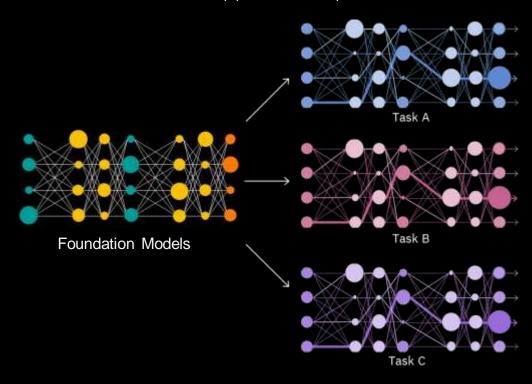


Why Foundation Models?

Classical AI models: Purpose-built and siloed



Foundation Models: One base supports multiple tasks



Why Foundation Models?



Less labeling means less effort and lower upfront costs



Effort mostly on fine tuning and inferencing means faster deployment



Equal or better accuracy than state-of-the-art for multiple use cases



Better performance means incremental revenue



Economy of scale drives the development of Foundation Models

NLP Foundation models are taking the world by storm





Foundation Models Are The New Public Cloud



Sting warns against AI songs as he wins prestigious music prize

Forbes

As AI Advances, Will Human Workers Disappear?

THE WALL STREET JOURNAL.

ChatGPT Fever Has Investors Pouring Billions Into AI Startups, No Business Plan Required

Amid broader venture-capital doldrums, it is boom times for startups touting generative artificial intelligence tech



Question – Can we develop "foundation models" for energy systems?

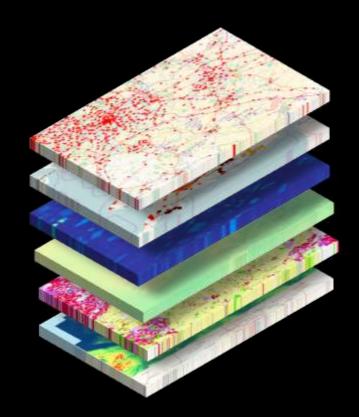
Al Energy systems go beyond text data

	Text
Downstream applications	High value & Many
Data availability	Available
Data type	Sequence
Data variety	Limited numbers of words
Context	Relative complete
Base Model	Grammar / rules
Architectures	Transformers

An important modality for energy systems is geospatial

- ✓ Weather
- ✓ Satellite imagery
- ✓ LIDAR point clouds
- ✓ AMI
- ✓ Drone imagery

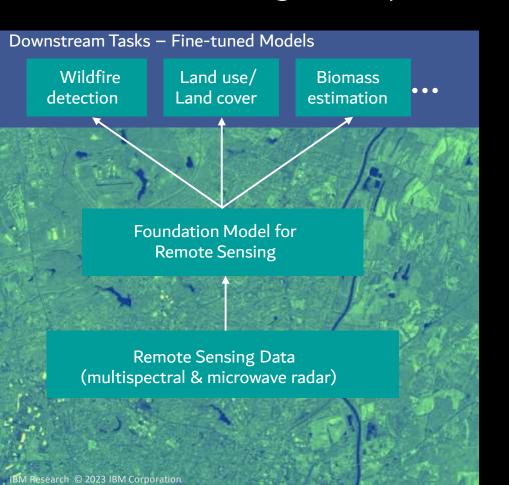
...and many others



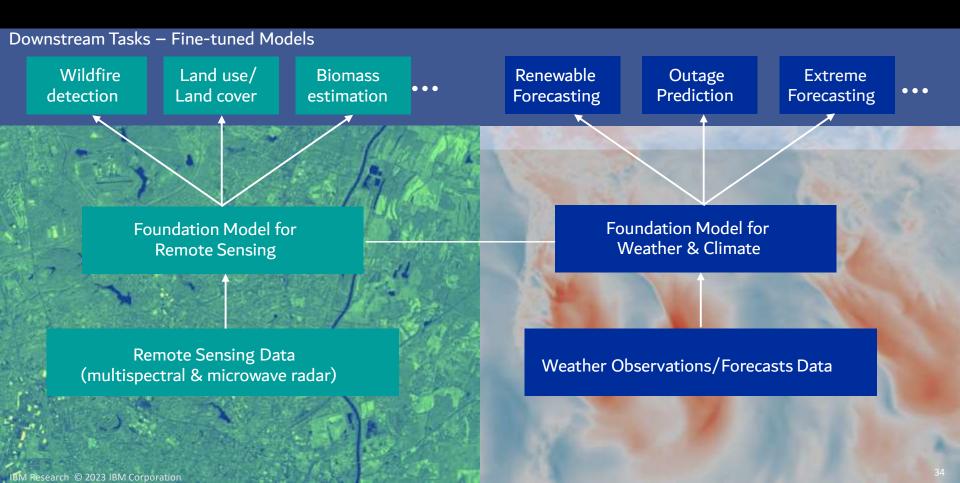
Al Energy systems go beyond text data

	Text	Geospatial/Weather		
Downstream applications	High value & Many	TBD		
Data availability	Available	TBD		
Data type	Sequence	Multi-modal, multi-dimensional		
Data variety	Limited numbers of words	TBD		
Context	Relative complete	TBD		
Base Model	Grammar / rules	NWP / Physics		
Architectures	Transformers	TBD: Transformers, Graphs, Operators		

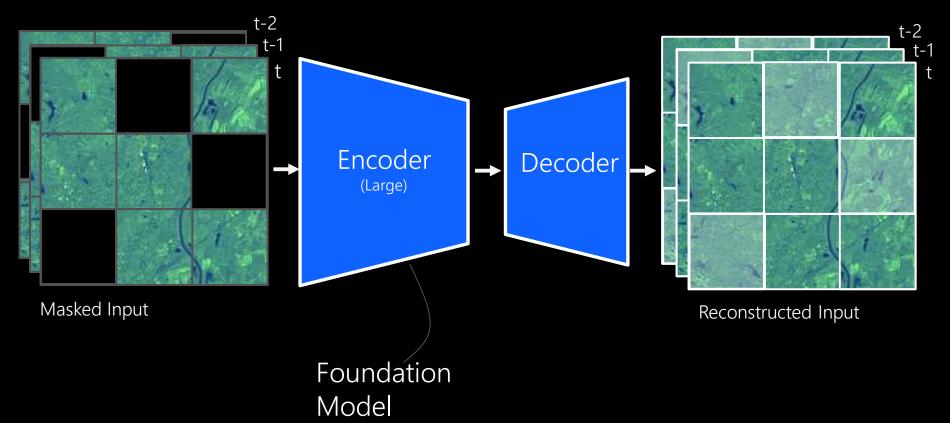
Building Geospatial Foundation Models



Building Geospatial Foundation Models



Self-supervised learning to build Foundational Models



Data sampling procedure



Selecting pretraining data

Requirement → *diversified* pre-training dataset.

- For a given region, images can look similar across time.
- Random sampling → can bias towards most common landscapes.

Intelligent sampling scheme based on *geospatial* statistics.

Sampling data from across US

Sampling scheme

- 1. Aggregate various geospatial statistics (land use, climate zone etc.).
- 2. Divide the region into groups based on these statistics.
- Sample data as equally as possible from each group.

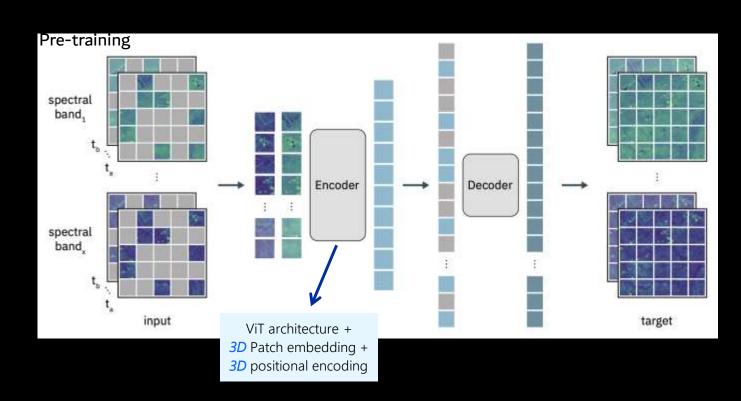
Model architecture (MAE = Masked AutoEncoder)

- Pre-training task: reconstruct masked patches → target = original data.
- MSE loss on masked patches.

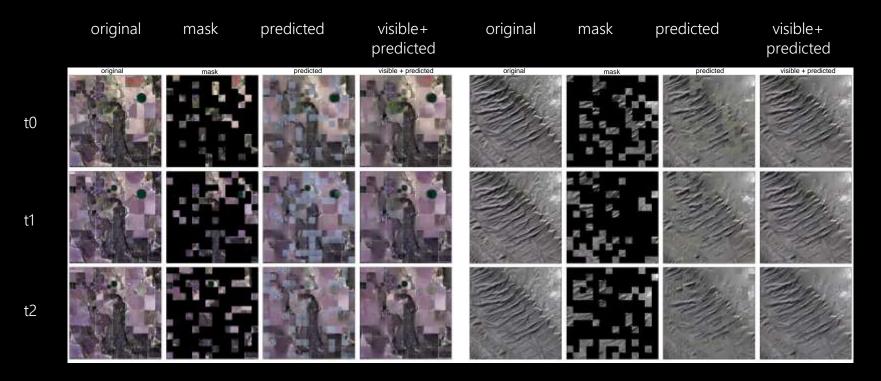
Encoder → Vision transformer (*ViT/Swin*) for multispectral *3D data*.

- 3D patch embeddings
- 3D positional encoding

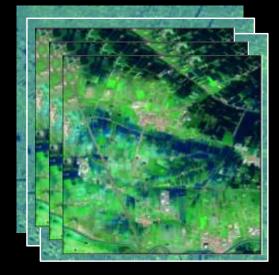
Decoder → Transformer blocks + linear projection layer to match the target patch size.



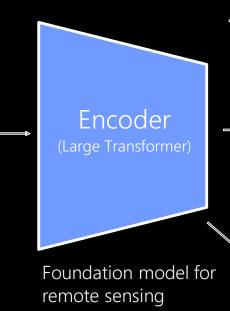
Pre-training results



Example fine-tuning workflow for satellite



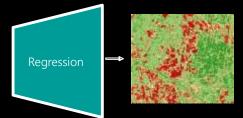
Input remote sensing data



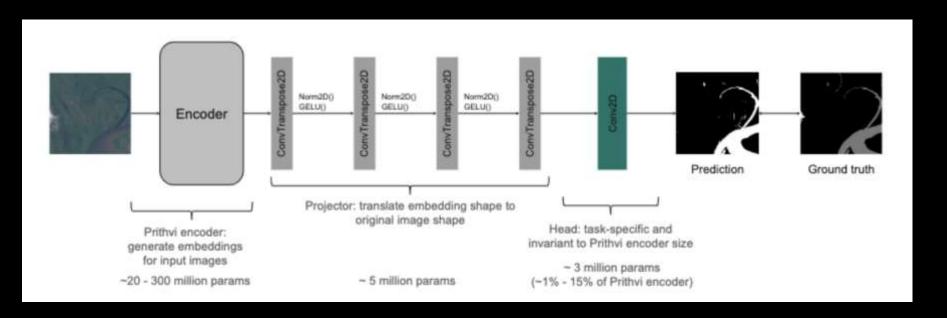


Wildfire detection

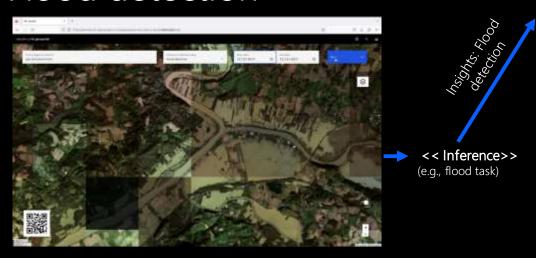
Above/Below Ground Biomass



Fine-tuning – Segmentation, classification and regression tasks

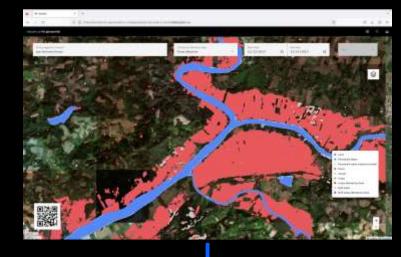


Inference insights: Flood detection



"Prompt": Image(s) (spatial + temporal domains)

	IoU (water class)	F1 (water class)	IoU	F1 score	Accuracy
Baseline [44]	24.21	-	-	87.	-
U-Net-based SOTA [45]	69.12	81.74	93.85	96.65	96.44
ViT-base [19] Swin [46]	66.52 74.75	79.89 85.55	90.92 92.38	94.97 95.90	94.97 94.73
Prithvi (not pretrained) Prithvi (pretrained)	79.23 80.10	88.41 88.95	94.52 94.78	97.09 97.23	97.07 97.23

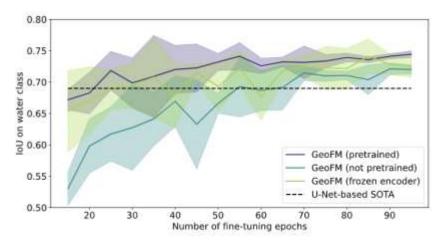


Insights: Flood impact

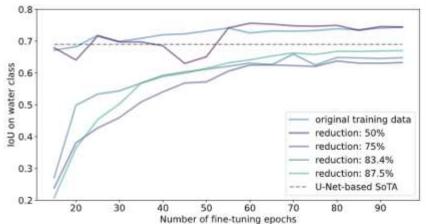


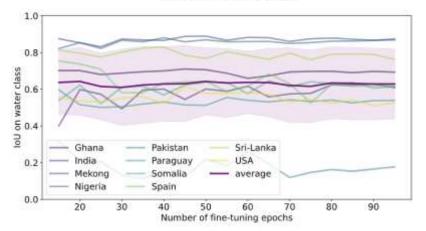
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Flood detection example - fine-tuning analysis



- ✓ Pre-trained model achieves higher IoU with a smaller number of training epochs and more consistently.
- ✓ It is robust to a reduction of 50% in the training data and performs consistently in most regions where it has not been trained.





IBM

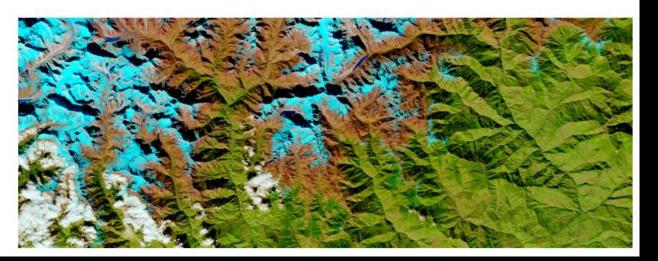




IBM and NASA Open Source Largest Geospatial AI Foundation Model on Hugging Face

Effort aims to widen access to NASA earth science data for geospatial intelligence and accelerate climate-related discoveries

Aug 3, 2023



Innovation and Research opportunities for Al and Foundation Models for energy systems

- What (high-value) downstream tasks need to be addressed?
- What content is required for pretraining, finetuning and inference?
- What is the pre-training/masking approach?
- What architectures are required?
- How to derive most efficiently knowledge from foundation models



Thank you